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Optimal fresh water blending: A methodological approach to improve the resilience of water supply systems

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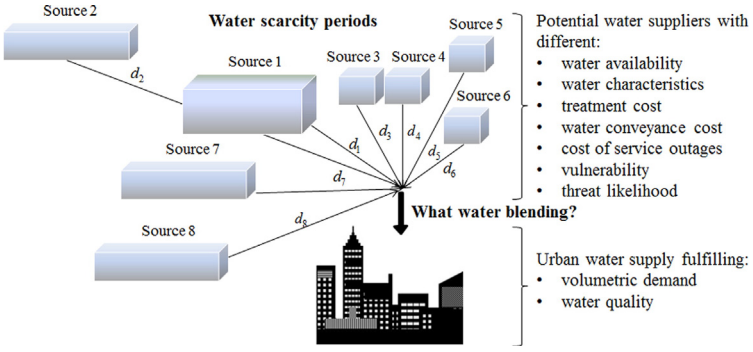
HIGHLIGHTS

- The diversification of water sources requires tools to optimize the blending options.
- ACO approach was proposed and applied to optimize the blending of water sources.
- Service outage, water conveyance and treatment costs were involved in the optimization.
- The proposal improves the resilience and sustainability of urban water supplies.
- The procedure achieves an optimal water blending at the overall lowest cost.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change and socioeconomic factors have increased the complexity of urban water supply systems. Thus, fresh water sources are being gradually diversified to improve the reliability and resilience of the systems. However, as the number of source blending options grows, optimization tools are needed to design drinking water supply systems that comply with indicators of cost, resilience, and water quality. This paper proposes a pioneering methodological approach, based on an ant-colony-optimization (ACO) algorithm, to optimize the blending of drinking water from different sources to minimize operational costs of a given system originating from a number of impaired water sources while complying with water quality standards. To evidence the potential of the ACO algorithm to solve such a system, a virtual case study was designed that considers eight fresh water sources, including seawater desalination and potable reuse. Seven scenarios were developed with different weightings to service outage, water conveyance and treatment costs while complying with water quality goals in regard to total organic carbon, nitrates, and total dissolved solids. It was shown that the cost per volumetric unit of water can vary considerably depending on the weightings of the three cost items. This paper provides a rigorous scientific approach to propose a methodology supporting the decision-making process of selecting a

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mixture of different sources to achieve the overall lowest system cost. Hence, this work contributes to improving the resilience and sustainability of urban water supplies.

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1. Introduction

Water scarcity is among the main problems faced by many societies worldwide in the 21st century. Currently, approximately 1.2 billion people live in areas of physical water scarcity, and 500 million people are approaching this situation (UNDESA, 2016). Climate change combined with other socioeconomic factors can reduce the availability of fresh water in urban areas (Liu et al., 2017). On one hand, the impact of climate change, which has been observed globally, includes changes in rainfall patterns, which are likely to greatly impact water availability and quality (Bangash et al., 2013). On the other hand, rapid population growth over the past 60 years has led to accelerated global urbanization. Thus, cities represent hotspots that place enormous pressure on freshwater supplies (Padowski and Gorelick, 2014). Hence, climate change and anthropogenic changes are expected to have dramatic impacts on global water availability and quality for human use (Boithias et al., 2014).

As a consequence of acute water scarcity and water quality degradation, water authorities and water utilities face the problem of ensuring the continuous supply of drinking water that meets quality standards (Li et al., 2016a). This challenge is even more complex to address when considering two key issues in water supplies: temporal dimensions and uncertainty in the quantity and quality of the fresh water. Traditional urban water supply systems were built through the combination of independent components. However, this traditional paradigm is no longer suitable to meet future challenges, and more reliable and resilient systems are needed (Gonzales and Ajami, 2017). Moreover, the unexpected trends and uncertainties posed by climate change increase the complexity of urban water supplies.

Regarding quantity issues, one of the first measures that water utilities should adopt to handle the problem of urban water supplies is to increase the diversification of fresh water sources (Di Matteo et al., 2017). Having a resilient urban water supply system has been identified as a key element of urban sustainability (Li et al., 2016b). Some years ago, most drinking water supply systems were fed by a single or only a few water sources (typically groundwater or surface water from lakes, rivers or reservoirs). In an uncertain context, this paradigm is changing, and drinking water supply systems are increasingly fed by a mixture of drinking water sources drawing upon climate resilient and/or impaired sources, such as low-quality groundwater, seawater requiring desalination or wastewater treatment plant effluents (Fielding et al., 2015). This increased diversity of raw water sources has led to the considerable development and diversification of available purification technologies. In addition to conventional systems, new technologies, such as different membrane filtration techniques, oxidation technologies, and granular activated carbon treatments, have become more common (Hayashi et al., 2008).

Literature provides a wide number of references (e.g. Wang et al., 2009; Kondili et al., 2010; Liu et al., 2011; Ashbolt et al., 2014) about optimal procedures for the management of water supply from multiple sources. Basically, these techniques are focused on the optimisation of economic, hydro-economic, social, environmental, and energetic aspects. For the context of large cities, like Los Angeles (USA) (Draper et al., 2003; Porse et al., 2017), Adelaide (AU) (Wu et al., 2017), and Tampa (USA) (Santana et al., 2017) the management system includes some optimization procedures, but they do not specifically consider fresh water quality parameters.

The variability in the quality of the raw water that feeds a drinking water treatment plant (DWTP) evidently impacts its design needs and operation (Li et al., 2014) from a technical and economic standpoint. Hence, the agency responsible for designing the water supply system must require the careful selection of an appropriate mix of raw water sources from a set of available drinking water sources with different qualities and located at different distances and adequate treatment technologies that can meet the desired and required drinking water quality standards while minimizing the overall costs. In other words, as the number of fresh water blending options grows, this task becomes an increasingly complex optimization problem that cannot be solved without advanced optimization tools.

Numerous studies have assessed the performance of different technologies to remove pollutants from fresh water and have optimized the operation of DWTPs under a set of scenarios (e.g. Luo et al., 2012; Loganathan et al., 2013; Sanchez et al., 2014; Lu et al., 2015; Lee et al., 2016). However, to the best of our knowledge, the issue of selecting the most suitable mix of raw water sources (with different qualities and from different locations, each treated with the appropriate and typical treatment approach) has not been previously addressed in the context of drinking water supply management. In this paper, we propose a new approach to address this problem in a systematic way, using a combinatorial optimization procedure, which belongs to the multidimensional (multiple constraints) knapsack problem category. This type of NP-Hard problem can be solved by metaheuristic methods (Voβ, 2001) such as the ant-colony-optimization (Dorigo and Blum, 2005). In our approach we use this ant-colony-optimization (ACO) algorithm, which was inspired by the behaviour of ants that use pheromone trails to guide their explorations (Dorigo and Di Caro, 1999; Dorigo and Stützle, 2004; Dorigo et al., 2006).

ACO algorithms have recently been applied to several complex water and wastewater management problems, such as watershed management, groundwater management, surface water management, reservoir operation, water distribution systems, urban drainage and sewer systems and storm water management. A summary of the existing studies in this field is provided by Afshar et al. (2015), who also evidenced that the ACO algorithms have proven to be a flexible and powerful tool for solving a number of spatially and temporally complex water resource problems in discrete and continuous domains with single and/or multiple objectives.

Against this background, the main objective of this paper is to propose a methodological approach based on an ACO algorithm that provides the optimal fresh water blending from a set of water sources with different qualities while minimizing the operational costs of DWTPs and complying with the constraints of water quality standards, in which each source does not necessarily comply with all the water quality criteria on its own. In other words, this paper proposes a methodological approach to improve the resilience of contributing water systems to ensure a high-quality and continuous supply of drinking water.

The algorithm selects the volume of fresh water from different sources with the aim of minimizing water supply cost based on three items: i) the cost of service outages based on the vulnerability of the source, ii) the water conveyance cost and iii) the water treatment cost. The considered water quality parameters and constraints for the algorithm are the concentrations of nitrates, total organic carbon (TOC), and total dissolved solids (TDS). These three parameters were chosen as they strongly impact the type of treatment required as particularly TDS and nitrate removal fundamentally change the treatment technology employed. Similarly, the TOC content is of great importance to disinfection as a high TOC concentration will mean that disinfectant stability in the distribution system decreases and undesired disinfection byproduct formation increases. It is noteworthy to state that while this may be an oversimplification compared to actual regulatory water

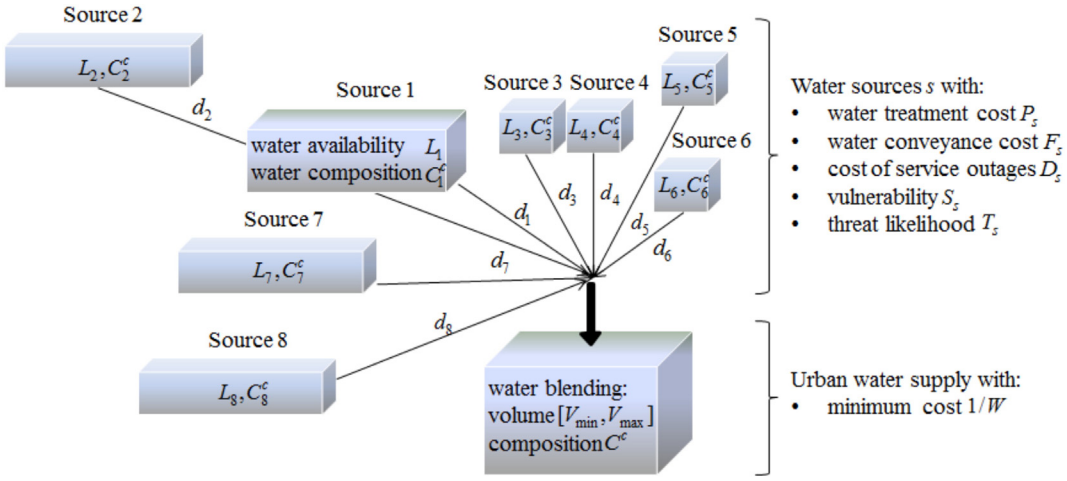

Fig. 1. Scenario of the case study.

quality requirements, the algorithm itself is flexible towards the inclusion of further constraints.To illustrate the usefulness of the proposed methodology for supporting decision-making processes, a virtual case study was developed. The case study simulates the decision-making process of selecting the most suitable mixture of fresh water from eight different sources of water, including surface water, groundwater, brackish groundwater, potable reuse water and seawater desalination water.

This paper contributes to the current literature by proposing, for the first time, an ACO algorithm to optimize the blending of fresh water while minimizing the operational costs of a given drinking water supply system consisting of up to eight treatment facilities that supply a distribution network after prior blending. Hence, this study introduces a novel approach in the framework of the sustainable and efficient design of drinking water supply systems in the context of water scarcity and the need for sourcing water from multiple impaired sources.

2. Materials and methods

2.1. Problem statement

A set of water sources W_s with $s \in \{1,\ldots,n\}$ constitutes the potential water suppliers of a hypothetical city A. Each source has its own reservoir and an associated treatment plant with a daily maximum treatment capacity L_s and is located at a distance d_s from the city's water distribution network. The treated water can be supplied as the volumetric contributions V_s^j, with $j \in \{0,\ldots,l_s\}$ that are selected as a multiple of a number (100) such that $100\ j = V_s^j$. Additionally, the treated water supplied to the city from each source is characterized by the concentrations of nitrates (NO_3^-), total organic carbon (TOC) and total dissolved solids (TDS), which are defined as the set of constraints C_s^c, with $c = 1, 2$ and 3, respectively. It is noteworthy that some of the available water sources do not comply with the required water quality criteria and hence require blending.

The water distribution system must supply a total daily volume of water in the range $[V_{min}, V_{max}]$ with a composition that cannot exceed the maximum allowed contents of NO_3^-, TOC and TDS, defined as the set of values C^c, with $c = 1, 2$ and 3.

The objective is to determine the combination of water contributions from the potential suppliers that shows a maximum volume collected per unit cost while also meeting the required water composition after blending of the mixture.

The function to maximize W (Eq. (1)) is expressed in water volume (m^3) per cost unit (€). It is composed of the sum of three terms related to different contributions to the total cost. The first term is correlated to the cost of service outages, the second with the cost of water conveyance, and the third with the cost of treating the water from each source,

$$W = \sum_{s=1}^{n} w_1 \frac{\sum_{j=0}^{l_s} y_s^j V_s^j}{D_s S_s T_s} + \sum_{s=1}^{n} w_2 \sum_{j=0}^{l_s} \frac{y_s^j V_s^j}{y_s^j \left(V_s^j F_s\right)} + \sum_{s=1}^{n} w_3 \sum_{j=0}^{l_s} \frac{y_s^j V_s^j}{y_s^j \left(V_s^j P_s\right)} \quad (1)$$

where w_1 is the weighting for the term describing the cost of service outages; y_s^j, the decision variables; V_s^j, the volume provided by the

Table 1
Case study values regarding the water sources and requirements for the total water supply.

Source		d_s (km)	L_s (m^3)	D_s (€)	S_s	T_s	F_s (€/m^3)	P_s (€/m^3)	C_s^c (g/m^3)		
									C_s^1	C_s^2	C_s^3
s_1	Surface water 1	10	10,000	20	4	0.10	0.1	0.4	5	4	200
s_2	Surface water 2	100	5000	20	5	0.15	0.8	0.2	5	2	200
s_3	Groundwater 1	10	2000	20	3	0.10	0.1	0.2	50	1	150
s_4	Groundwater 2	10	2000	20	3	0.10	0.1	0.2	50	1	150
s_5	Groundwater 3	20	2000	20	3	0.15	0.2	0.2	200	1	1000
s_6	Brackish groundwater	10	2000	20	3	0.25	0.2	0.7	0	1	100
s_7	Potable reuse	20	5000	20	2	0.05	0.2	1.0	5	1	50
s_8	Seawater desalination	30	5000	20	1	0.03	0.3	1.2	0	1	100
Requirements (for the total water supply)			$[V_{min}, V_{max}]$ [20000, 25000]						C^1 ≤30	C^2 ≤2	C^3 ≤200

source s to the water distribution system; D_s, the daily cost of service outages; S_s, the vulnerability of the source s; T_s, the threat likelihood; w_2, the weighting assigned to the term related to the conveyance cost; F_s, the conveyance cost per unit of water volume; w_3, the weighting assigned to the term related to locally obtaining water s; and P_s, the cost of the treatment per volume unit of each source s.

The objective function is constrained by the required volume (Eq. (2)), the maximum admissible concentration values of NO_3^-, *TOC* and *TDS* (Eqs. (3)–(5), respectively) in the total water supply, and the sum of the decision variables (Eq. (6)).

$$\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j \in [V_{\min}, V_{\max}] \tag{2}$$

$$\frac{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j C_s^1}{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j} \le C^1 \tag{3}$$

$$\frac{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j C_s^2}{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j} \le C^2 \tag{4}$$

$$\frac{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j C_s^3}{\sum_{s=1}^{n}\sum_{j=0}^{l_s} y_s^j V_s^j} \le C^3 \tag{5}$$

$$\sum_{j=0}^{l_s} y_s^j = 1, \text{with } s = 1, 2, ..n \tag{6}$$

2.2. Defining the scenarios

The proposed methodological approach was applied to a virtual case study that involves the supply of drinking water from eight water sources (see Fig. 1).

Table 1 shows the different potential suppliers considered, their distances from the distribution system, the different unitary costs involved in the final cost of the water, the different water compositions, and the requirements for the total water supply. The values of F_s and P_s were obtained from the general literature as plausible expenditures for water conveyance and treatment associated with the respective water sources (Crittenden et al., 2012). The values of S_s and T_s were allocated taking into account that the vulnerability of the water source is understood as the sensibility of the water source to be affected by non-anthropogenic factors resulting in a failure in meeting urban water supply demand and the threat likelihood measures the impact of threats such as droughts, floods and pollutant events on water availability and quality.

To assess the decision-making preferences, seven scenarios were simulated that differ in the values assigned to the weightings w_1, w_2, and w_3 (Table 2). Weighting assigns more or less importance to each term considered when achieving a solution. The weightings consider the influence of the cost of service interruption, the cost of water transport and the cost of water treatment of each source in the value obtained for W. The reference scenario uses the same value for the three weightings. In this scenario, the values of the three terms of W show large differences (1:1/257:1/494) in relation to their respective contributions to the achievement of the solution value. Scenario 1 assigns the same importance to the three terms (1:1:1) by using different values for the weights. Scenario 2–4 then prioritize either treatment cost or transport cost compared to each other. Scenario 5 then resembles a scenario, where system reliability is strongly prioritized, i.e. where a high cost is associated to failure of delivery of service, even if that may not necessarily be a true cost incurred but rather a perceived loss of image. Scenario 6 would be the opposite, i.e. delivery of the service at least cost complying with the water quality constraints fulfilled but without accounting for any incurred cost related to failure to deliver water.

Table 2
Scenarios in the case study.

Relation of the costs contributing to W service outage:transport:treatment	Weighting			Scenario
	w_1	w_2	w_3	
1:1/257:1/494	0.33	0.33	0.33	Reference
1:1:1	0.0013	0.3418	0.6569	1
1:0.5:0.5	0.0027	0.3413	0.6560	2
1:1:0.5	0.0020	0.5089	0.4891	3
1:0.5:1	0.0016	0.2061	0.7923	4
10:1:1	0.0131	0.3377	0.6492	5
0:1:1	0.0000	0.3422	0.6578	6

2.3. Ant-colony-optimization algorithm

The ACO algorithms (Dorigo and Stützle, 2004; Dorigo and Blum, 2005) use virtual ants to perform an iterative and stochastic procedure to achieve an optimal solution, emulating the behaviour of real ants in their search for food. Real ants leave a pheromone trail along the path they follow that leads to food. Then, new ants emerging from the nest will sense paths with different pheromone trails. Their tendency will be to follow the paths with large amounts of pheromone. As the number of ants emerging from the nest increases, the number of ants finding food will increase. In similar way, virtual ants (Dorigo et al., 1996; Cordón et al., 2002) follow a probabilistic rule to decide their paths. When an ant completes a path that leads to a feasible solution, it leaves a 'pheromone trail'. The pheromone trails are regulated by a global update rule that also considers the quality of the solution achieved from the path. The number of ants following the paths with larger amounts of pheromone increases as the iterations progress. At the end of the iterations, the ants will achieve an optimal solution.

The ACO algorithm proposed to solve the combinatorial optimization problem in this work is an adaptation of the Max-Min Ant System (Stützle and Hoos, 2000). Stützle and Dorigo (2002) demonstrated the convergence to an optimal value of the solution found for this algorithm. Basically, the approach differs in the type of NP-Hard problem. The water supply problem is viewed as a multidimensional knapsack problem, in a framework similar to that of Verdaguer et al. (2014), and with a representation of the space of solutions that admits different possibilities of water supply for each source. The final path followed by the ants will be composed of a sequence of water contributions from the different sources and will be related to an optimal solution.

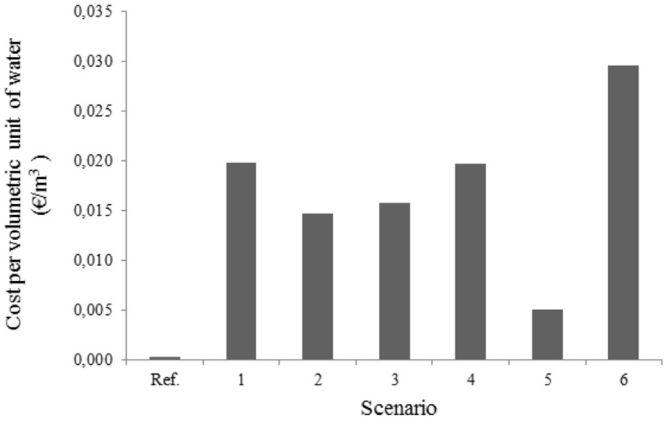

Fig. 2. Results of cost per volumetric unit of water achieved in the reference scenario and scenarios 1 to 6. The minimum cost was achieved in the reference scenario.

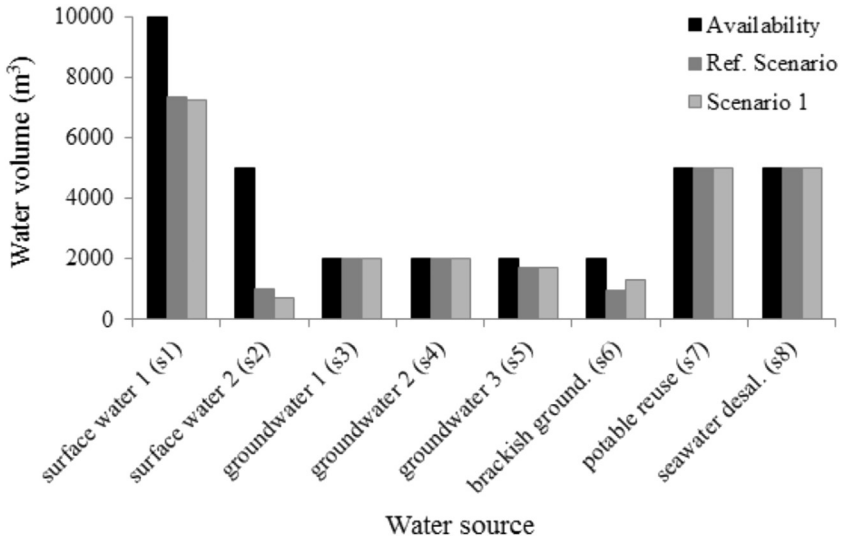

Fig. 3. Water supply volumes in the reference scenario and scenario 1. Each source contributed with a similar water supply in both scenarios, with values close to the available volume, with the exception of the sources s1, s2, and s6.

In each iteration of the algorithm, the movement of ants is determined by the state transition rule (Dorigo et al., 1996; Cordón et al., 2002; Dorigo and Blum, 2005). This rule uses the amount of pheromone determined after updating the values corresponding to the iteration $t-1$ (using the specific updating rule).

The state transition rule at iteration t is defined by Eq. (7),

$$p_{sj}^{m}(t) = \frac{[\tau_{sj}(t)]^{\alpha}\left[h\left(V_{sj}/C_s^c\right)\right]^{\beta}}{\sum_{l=0}^{l_s}[\tau_{sl}(t)]^{\alpha}\left[h\left(V_{sl}/C_s^c\right)\right]^{\beta}} \tag{7}$$

where p_{sj}^{m} is the probability that the m^{th} ant selects the volumetric supply V_s^j; τ_{sj}, the pheromone amount; α, the importance assigned to the pheromone amount; $h\left(V_{sj}/C_s^c\right)$, the heuristic information that helps the ants find greater volumes and lower concentrations of water components c, where $c = 1$, 2 and 3; and β, the importance assigned to the heuristic information.

Eq. 8 defines the specific heuristic information used in this problem,

$$h\left(V_{sj}/C_s^c\right) = \frac{V_{sj}}{\sum_{c=1}^{3}(C_s^c * 0.33)} \tag{8}$$

The rule to update the pheromone value is determined by Eq. (9) (Stützle and Hoos, 2000)

$$\tau_{sj}(t+1) = \rho\tau_{sj}(t) + \Delta\tau_{sj}^{best}(t) \tag{9}$$

where $\tau_{sj}(t+1)$ is the amount of pheromone at the beginning of iteration $t+1$, the value of which is in $[\tau_{\min}, \tau_{\max}]$ (Stützle and Hoos, 2000; Verdaguer et al., 2016a); ρ, the coefficient of trail persistence, which has a value in $[0,\ 1]$; and $\Delta\tau_{sj}^{best}$, the increase in the amount of pheromone assigned to the ant that achieved the best solution W^* at iteration t, with $\Delta\tau_{sj}^{best} = W^*(t)$ (Verdaguer et al., 2014, 2016b).

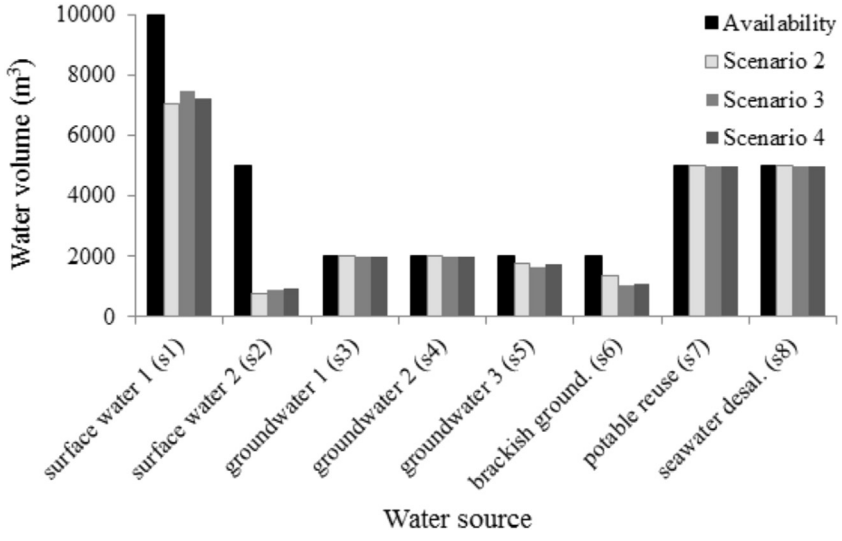

Fig. 4. Water supply volumes in scenarios 2, 3 and 4. For these scenarios, the relation of the costs of service outage-conveyance and treatment was 1-0.5-0.5, 1-1-0.5, and 1-0.5-1.

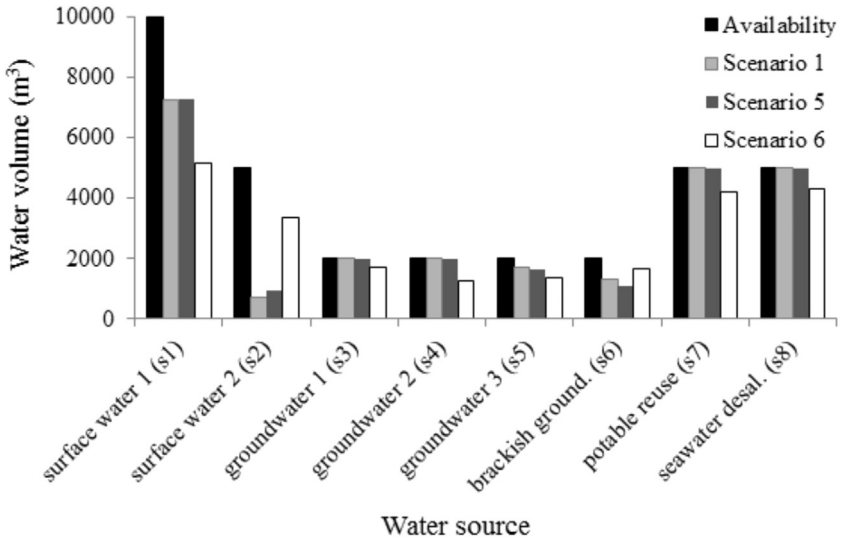

Fig. 5. Water supply volumes in scenarios 1, 5 and 6. Scenario 6, which does not consider the service outage cost, showed the smallest volumes of water contributions, except for those obtained from the sources s2 and s6.

2.4. Simulation methodology

The case study simulations were executed using an Intel Core i7-582K processor (3.30 GHz) with 16 GB of RAM.

All simulations were performed by executing 10 repetitions of the algorithm. The results obtained were averaged because of the probabilistic procedure of the algorithm. Each repetition was composed of 500 iterations (Nahas and Nourelfath, 2005), and each iteration was carried out by 100 ants. The algorithm parameters used were $\alpha = 1$, $\beta = 2$ (Verdaguer et al., 2014, 2016a, 2016b), and $\rho = 0.98$ (Stützle and Hoos, 2000; Favaretto et al., 2009).

3. Results and discussion

The results obtained in the simulations executed using the proposed ACO algorithm demonstrate its usefulness for determining the combination of different water contributions that provide the minimum cost per volumetric unit of a water supply. This value corresponds to the inverse of the maximum value achieved for the objective function. Fig. 2 shows the economic cost (€) of supplying one cubic metre of water in the different scenarios. The executions in the reference scenario provided the minimum value. In this scenario (with $w_1 = w_2 = w_3 = 0.33$), the cost per volumetric unit of water (0.000236 €/m^3) showed a 20.1-fold decrease in relation to the value obtained in scenario 5 (which showed the second lowest value, 0.00499 €/m^3) and a 123.6-fold decrease in relation to the value obtained in scenario 6 (which showed the highest value, 0.02948 €/m^3). It should be noted that scenario 6 ignores the cost of service outages and allocates larger weightings to the water conveyance cost and water treatment costs. In scenario 5, the solution was 1.9 times lower than the value achieved in scenario 2 and 4.9 times lower than that obtained in scenario 6. Hence, the values attained in the different scenarios evidence the importance of the weightings allocated to the different terms in Eq. (1).

In all executions, the returned solution W is related to a sequence of volumetric water contributions. For each execution, the sequence is composed of a single contribution (including zero contribution) from each source. The algorithm performs a maximization process to obtain a sequence with a maximum volume of water supply per unit of total cost. For the executions performed in the reference scenario and scenarios 1 to 5, the total volume achieved was equal or approximate to the maximum required (25,000 m^3). In scenario 6, the total volume (22,960 m^3) does not reach the maximum value, but it is in the required range of volume values. Note that this algorithmic behaviour is consistent with the proposed approach.

The comparison of the different individual volumetric contributions of the sources through the different scenarios evidence the dominant role in Eq. (1) of the term related to the cost of the service outage time. In the reference scenario and scenarios 1 to 5 (Figs. 3–5), each source contributed a similar volume in each scenario. The sources s_3, s_4, s_5, s_7, and s_8 (groundwater 1, groundwater 2, groundwater 3, potable reuse, and seawater desalination) showed values equal or very close to their respective maximum water availability. These sources exhibited the smallest values of vulnerability S_s (Table 1). However, source s_6 (brackish groundwater) supplied a volume lower than its maximum availability. This source had a small S_s value but also presented the highest P_s value (cost per unit of obtaining water from the source itself). A similar behaviour can be observed for the contribution from s_2 (surface water 2), which was located at the greatest distance from the distribution system. Therefore, this source was related to the highest value of F_s. In scenario 6, the algorithm obtained the smallest volumes contributed from each source, excluding s_2 and s_6. In all scenarios, the contributions achieved from these last sources, s_2 and s_6, evidence the importance of also considering the cost of water conveyance and the cost of obtaining water from each source.

As reported in the introduction, the aim of the proposed methodology was to optimize fresh water blending from a quantitative and qualitative standpoint. Table 3 shows the compositional characteristics of the total water supply in all scenarios. For all executions, the composition obtained fulfils the corresponding constraints. The reference

Table 3
Results of the concentrations in the total water supply.

Scenario	NO_3^- (g/m^3)	*TOC* (g/m^3)	*TDS* (g/m^3)
Reference	24.24	1.92	192.59
1	24.34	1.90	191.82
2	24.82	1.88	193.52
3	23.63	1.93	189.72
4	24.65	1.91	193.94
4	23.76	1.91	190.07
6	20.91	1.82	186.98

scenario and scenarios 1 to 5 obtained similar concentrations for the three pollutants involved in the assessment. By contrast, scenario 6 showed the lowest concentrations of pollutants and therefore the best water quality. This scenario presented a decrease of 3.33 g/m^3, 0.09 g/m^3, and 4.96 g/m^3 in the concentration values of NO_3^-, *TOC*, and *TDS*, respectively, in relation to those achieved on average in the reference scenario and scenarios 1 to 5. This difference is due to the different profiles shown by the volumetric contributions from the sources.

From a policy perspective, the methodology and results of this study are of great interest for DWTP managers and water authorities (water regulators). On one hand, the proposed methodology will facilitate the decision process of selecting the blending of fresh water to fed DWTPs. Since the objective of the proposed methodology is to minimize the operational costs of DWTPs, water regulators and citizens will also receive benefits of fresh water blending optimization. Thus, in many countries, such as the UK, Portugal, the Netherlands and Chile, where the water industry is regulated, the process to review tariffs is based on the estimation of investment costs and operational and maintenance costs to supply drinking water to customers (Molinos-Senante et al., 2016). Since this paper contributes to the minimization of the operational costs of DWTPs, it also provides insight to keeping water tariffs as lowest as possible.

4. Conclusions

Due to climate change and accelerated global urbanization, many societies are facing water scarcity and quality problems, which are far from being solved. In this context, traditional urban water supplies based on the combination of independent components is no longer suitable. By contrast, more reliable and resilient systems are needed, which requires the diversification of fresh water sources that fed DWTPs. However, as the number of fresh water blending options grows, optimization tools are required to select the most suitable combination. This paper proposes a methodology based on the ACO algorithm to optimize the blending of fresh water sources to minimize DWTP operational costs while meeting water quality standards.

To illustrate the usefulness of the proposed methodological approach, a virtual case study was developed, which included eight fresh water sources with variable characteristics that impact on the operational costs of the water supply, namely, i) the distance from the source to the DWTP, ii) the vulnerability of the source, iii) the threat likelihood, iv) the cost of the raw water, and v) the concentrations of NO_3^-, *TOC* and *TDS*. The behaviour of the algorithmic procedure shows the importance of the following items:

- the values of weightings w_1, w_2, and w_3 in the achievement of the minimum cost per volumetric unit of water supply. From an economic perspective, the best option among those studied was to use the same value ($w_1 = w_2 = w_3 = 0.33$) for all weightings;
- the consideration of the term related to the cost of service outages in the objective function. This term plays a dominant role in achieving the maximum total volume of water supply and in the determination of the contribution profile of the sources;
- obtaining the smallest vulnerability values for achieving the greatest individual contributions from the sources, followed by the cost of obtaining water from the source itself and the cost of water conveyance.

This paper evidences the utility of ACO algorithms to successfully address the complex problem of selecting the most suitable mixture of fresh water sources. Moreover, the results illustrate the importance of including social and resilience-related variables, such as the service outage time and the vulnerability of the water source, in the optimization. The demonstrated empirical application showed the usefulness of the proposal as a new contribution to improving the resilience and sustainability of urban water supplies.

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